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UV, VIS, AND NIR PROPERTIES OF PEANUT KERNELS

by

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Summary:

Spectral characteristics of peanut kernels were measured using ultraviolet, visible, and infrared sensors. The spectral information allowed kernels to be classified into categories based on their spectral characteristics. Qualitative and quantitative quality information of peanuts in each category then indicated the effectiveness of identifying poor quality peanuts using various optical sensors. The accuracy of various sensors when identifying poor quality peanuts is reported.

Keywords:

Grading, quality, inspection, aflatoxin

INTRODUCTION

Trained inspectors annually determine peanut (*Arachis hypogaea*, L.) quality by visually inspecting samples from each of the 600,000 lots of farmer-marketed peanuts as part of the peanut grading and marketing process. When the inspector observes specific types and amounts of discoloration on the shelled peanuts, the inspector removes the damaged kernel and later determines the percentage by weight of damaged kernels in the sample. The amount of damaged kernels present affects the price received by the seller and dictates whether the peanuts can be used in edible products. The subjectivity involved in making this grade determination contributes to the inaccuracy of the grading process by inducing human error (Dowell, 1992a). If the inspector misclassifies a good quality peanut kernel, then undue penalties are applied to the seller. If the inspector misclassifies a bad quality peanut kernel, then poor quality peanuts may reach the edible market. Preventing these poor quality peanuts from reaching consumers is especially important as the peanut industry seeks to meet stricter tolerances on aflatoxin levels. In addition, peanut industry groups such as the National Peanut Council, Federal State Inspection Service, and Southeastern Peanut Shellers Association, request the grading system be made less subjective and less laborious. Thus, an objective means of identifying damaged peanuts in grade samples is needed.

Spectral reflectance technology provides several means of replacing visual inspection with sensors. Sensors currently used by many industries include ultraviolet (UV), visible (VIS), and infrared (IR). Use of these sensors by industries such the automotive, pharmaceutical, and food processing (Farsaie et al., 1978; Ferraz et al., 1991) industries usually involves coupling a sensor with a product reject mechanism to sort defective products on-line from a stream of good products. When an inferior product is detected, it is removed from the good product by an air blast, trip gate, or other suitable means. The problem of identifying poor quality peanuts in grade samples is somewhat unique in that samples are only about 500 g in size and, to be economically feasible, sensor cost must be limited to about $1000 per unit. One or more sensors is needed at each of the approximately 500 grading locations throughout the peanut producing area. The purpose of this research was to determine the potential of UV, VIS, and IR reflectance sensors to detect damaged peanuts. If acceptable accuracy is obtained, subsequent research will focus on developing an economical sensor for grading rooms.

PROCEDURES

Approximately 1000 Runner-type peanut kernels from 1989 and 1990 crop years were stored in a kernel bank for subsequent analysis. The kernel bank contained individual cells to allow unique identification of each kernel. The bank included undamaged redskin and blanched kernels in addition to kernels from each of the following damaged kernel categories: freeze damaged, black spots, entirely black, brown, insect holes, *Aspergillus flavus*, white mold, purple seed coats, and yellow discolorations. Individual kernels were removed from the kernel bank and placed in the viewing area of each sensor. Analysis of the data allowed evaluation of each sensor.

SENSORS

The sensors tested spanned the spectral range from about 366 nm to about 1700 nm and included a UV sensor (366 nm), a spectrophotometer (400 - 700 nm), a colorimeter, and a NIR instrument (400 - 2500 nm).

ULTRAVIOLET SENSORS

Aflatoxin fluoresces at about 366 nm, thus testing of this UV region indicated if fluorescence at this wavelength correlates with aflatoxin levels. Instrumentation for the UV testing included a Model UVSL-58 Mineralight Lamp Multiband UV-254/366 nm in a Chromato-Vue Model 00-10. Testing occurred in 1988 and included about 10 kernels from each of 4 kernel categories: (1) Visibly discolored kernels with no fluorescence; (2) visibly good kernels with no fluorescence; (3) slight visible discolorations with some greenish or other fluorescence; and (4) visibly discolored and strong greenish fluorescence. Kernels were placed in the Chromato-Vue and hand sorted into the above kernel categories.

VISIBLE WAVELENGTH SENSORS

Visible wavelength tests were conducted during 1990 - 1992 using a Minolta Chroma Meter CR-200 and an X-Rite 968 reflectance spectrophotometer which measured kernel spectral reflectance from 400 nm to 700 nm in 10 nm intervals. The spectrophotometer specifications include a 0 degree illumination angle, 45 degree viewing angle, and an 8 mm diameter target window. Kernels were hand placed under the sensor with the darkest area of the kernel under the target window.

The CR-200 Chroma Meter measured kernel hue, saturation and intensity. The CR-200 specifications include an 8 mm diameter measuring area and a built-in xenon arc lamp. L*a*b*, L*C*H°, and Yxy color space coordinates measured by the colorimeter approximate the response of the human eye to color. Both the Chroma meter and spectrophotometer calibrations included using CIE illuminant C. The CR-200 measured color information from individual kernels placed in a glass specimen plate directly over the viewing area.

NEAR-INFRARED SENSORS

Two separate IR tests determined the applicability of IR to determining kernel damage. One test examined the use of thermal images to distinguish between damaged and undamaged peanuts kernels. Kernels were heated and the thermal images examined as the kernels cooled to see if the heat transfer coefficients of undamaged and damaged kernels differed. Previous inshell peanut research (Morita et al., 1992) indicates this procedure might be applicable to sorting undamaged and damaged peanut kernels. The second test involved measuring the VIS-NIR spectra of kernels over the range of 400 to 2500 nm. Spectral curves were obtained from 5-10 kernels from each of the following kernel categories: undamaged blanched and redskin, white mold, purple seedcoats, black spots, insect hole, green mold, black redskins, light brown, yellow, freeze damaged, dark blanched, and white moldy spots on redskins. Kernels were placed by hand in front of a fiberoptic probe attached to the infrared sensor.

DAMAGED KERNEL CLASSIFICATION

Kernel classification techniques included: visually noting fluorescence or differences in spectral curves; selecting thresholds at specific wavelengths or color space values at which optimum classification of kernels occurred; and using a neural network to classify kernels based on their spectral curves. Neural networks are being studied as classification tool for grading other commodities (Davidson and Lee, 1991; Thai et al., 1991).

Fluorescing kernels were visibly sorted into damaged kernel categories based on the presence, or absence, or fluorescence. Subsequent aflatoxin tests indicated the correlation of fluorescence to quality.

Optimum visible wavelengths (400 - 700 nm) and color space values that resulted in maximum classification of undamaged and damaged kernels were selected in previous research (Dowell, 1992b). Statistical tests revealed which values resulted in optimum kernel classifications. Additional kernel classification utilizing all visible spectral information occurred using a back propagation neural network by NeuroShell. A study of the effect of the number of nodes (1, 20, 40), learning rate (0.1, 0.6 0.9), momentum (0, 0.45, 0.9), and learning events (26,000, 520,000, 1,000,000) on kernel classification allowed selection of network parameters that resulted in optimum classification of undamaged and damaged kernels. Network training occurred on 1600 kernels and the test data set consisted of 44 undamaged and 112 damaged kernels.

NIR spectral curves from undamaged and damaged kernels were examined visibly to determine if curves were markedly different at specific wavelengths as part of a preliminary study to see if further research is warranted.

RESULTS

RESULTS USING ULTRAVIOLET SENSORS

In study 1 (Table 1), fluorescing peanuts were much higher in aflatoxin than nonfluorescing peanuts. However, Study 2 shows little difference between fluorescing and nonfluorescing peanuts. Research by other scientists (Pelletier and Reizner, 1992) since completion of this study confirms the weak correlation of aflatoxin to fluorescence. Although aflatoxin fluoresces, so do many other compounds. Thus, the observed fluorescence may have been due to any of a number of compounds. In addition, if the aflatoxin contamination was on an unexposed portion of the kernel, then the fluorescence would not have been observed. UV detection of aflatoxin is used to grade farmer-marketed corn, however, that applicability of this technology to peanuts is questionable.

RESULTS USING VISIBLE SENSORS

Table 2 summarizes results obtained when classifying kernels using the colorimeter and spectrophotometer. As expected, the kernel classification method utilizing the full spectral curve from the spectrophotometer correctly classified the largest percentage of total kernels. However, this is the most hardware and software intensive procedure. A neural network was used to increase classification accuracy.

Table 3 summarizes the neural network analysis of the spectral data when varying the number of nodes, learning rate, momentum, and learning events. Significant differences were not obtained in all cases, but trends in the data show that a low momentum, high learning rate, and a high number of learning events provided better damage classification. Further statistical analysis showed that the interaction of nodes and learning rate was significant (P=0.10). The best classification occurred when using 40 nodes, a learning rate of 0.6, a momentum of 0.45, and learning events of 520,000 or 1,000,000. These parameters resulted in correct classification of 82% of the undamaged kernels and 90.6% of the damaged kernels.

None of the methods classified the kernels with an accuracy acceptable to the peanut industry. In addition, the spectrophotometer and colorimeter are cost prohibitive. Initially, it was assumed that if the results from the 3 wavelengths were similar to those generated by the full spectral curve, that a low cost sensor filtered at the 3 selected wavelengths could be built to identify damaged peanuts. However, the poor results show that this is not worth pursuing since the classification accuracy needs to be in the upper 90% range. Thus, wavelengths outside of the visible spectrum were examined.

RESULTS USING NEAR-INFRARED SENSORS

Preliminary research was conducted to determine if wavelengths outside the visible spectrum could be used for damaged kernel classification. Our NIR research thus far has been limited to observing spectral curves and thermal images from a few kernels to determine the feasibility of an extensive NIR research thrust. Since previous research in thermal imaging of peanut pods (Morita et al., 1992) indicated that damaged pods could be identified using this method, a small scale study was undertaken to determine if the method works for kernels. However, observing thermal images of undamaged and damaged kernels in our limited research indicated that damaged kernels could not be identified using this method.

The NIR spectral curves of undamaged and damaged kernels did indicate some differences at specific wavelengths, especially around 1700 and 1900 nm. This difference is likely due to the oil or moisture content of the peanuts. Additional replication and further analysis of the spectral data is needed before sound conclusions can be drawn.

SUMMARY

Results from this and other research indicate that UV sensors may not offer consistent identification of kernels contaminated with aflatoxin. VIS sensors combined with neural networks achieved classification accuracies up to about 90%. Initial investigation using NIR sensors indicates further research is warranted. Additional research will focus on collecting and analyzing NIR spectra of undamaged and damaged peanut kernels.

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Table 1. Relationship of aflatoxin level to fluorescence in peanut kernels.

Kernel Category	Aflatoxin Level (ppb)
Study 1	
Not discolored - No fluorescence	0.4
Discolored - No fluorescence	2.3
Slight fluorescence	10,205.8
Strong fluorescence	4,948.6
Study 2	
No fluorescence	2.8
Strong fluorescence	6.9

Table 2. Classification of undamaged and damaged peanut kernels using a colorimeter, three wavelenghts measured using a spectrophotometer, and the spectral curves generated from a spectrophotometer. The spectral curves were compared using a neural network.

Sensor Type	Undamaged Correct (%)	Damaged Correct (%)	Total Correct (%)
Colorimeter	78.0	84.9	83.0
Spectrophotometer - 3 wavelengths[1]	98.0	63.2	74.4
Spectrophotometer - spectral curve[2]	82.0	90.6	87.8

[1]Wavelengths used were 450, 520, and 670 nm.
[2]The spectrophotometer had a 10 nm bandpass and spanned the region from 400 to 700 nm.

Table 3. Results from a neural network analysis of spectral curves.

Variable	Undamaged Correct (%)[1]	Damaged Correct (%)[1]	Total Correct (%)[1]
No. Nodes			
1	36.2b	92.2a	74.2a
20	46.9a	85.9a	73.4a
40	41.7ab	90.4a	74.8a
Momentum			
0	41.8a	90.9a	75.2a
0.45	46.2a	88.4a	74.9a
0.9	36.8a	89.2a	72.4a
Learning Rate			
0.1	37.0a	91.1a	73.8a
0.6	43.2a	91.1a	75.7a
0.9	44.5a	86.3a	72.9a
Learning Events			
26,000	32.8b	91.1a	72.4b
520,000	43.6a	87.7a	73.6ab
1,000,000	48.3a	89.7a	76.6a

[1]Means for each variable in columns followed by the same letter are not significantly different at P=0.05. Mean values for each variable are averaged across the other three variables (i.e., average value for number of nodes are averaged across all momentums, learning rates and learning events).